Week 12: Homework 2: Project: Chapter 7: Building Predictive Analytics For AWS IoT

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Github Repository: https://github.com/mkhan-sfbu/AWS-IoT-Raspberry-Pi-Emulator-Sensor-HAT-Emulator-Predictive-Analysis

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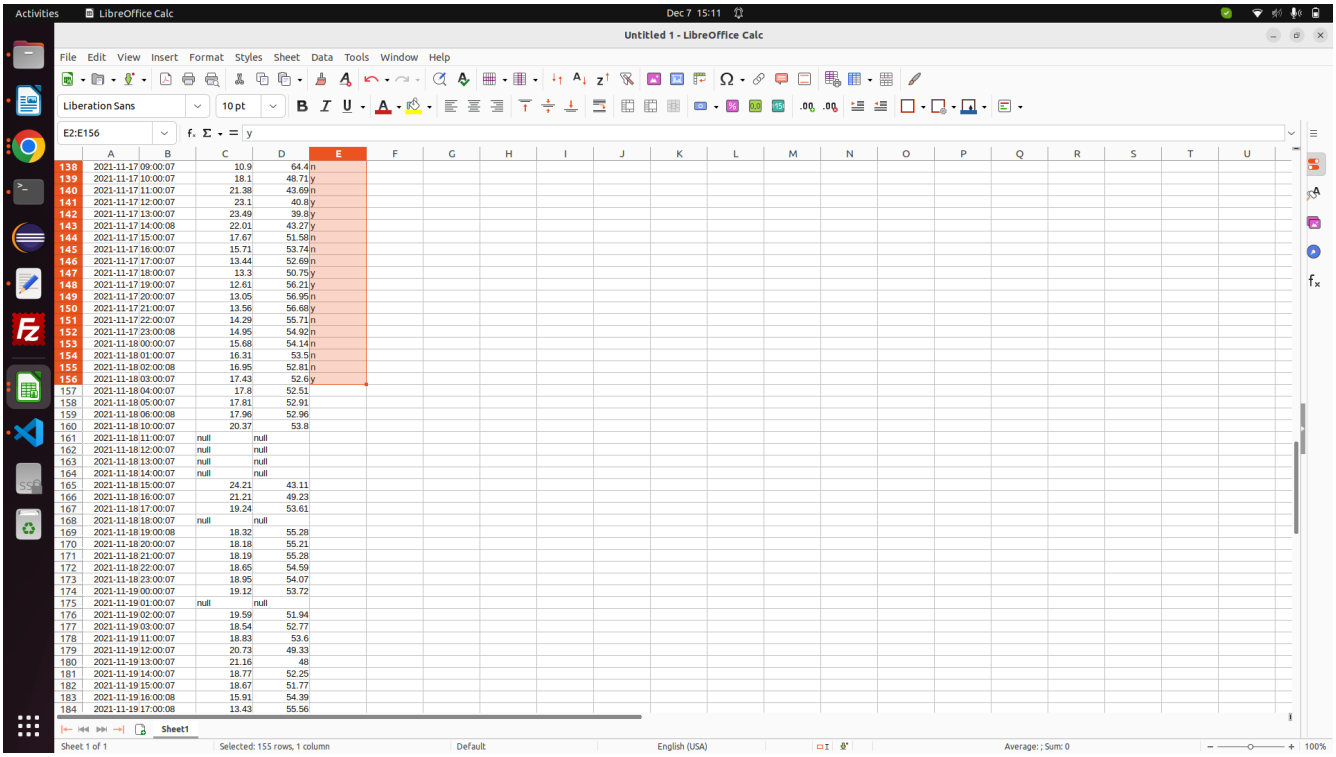
In this homework, we will use machine learning mechanism which is predictive analytics. We are going to use AWS to take a decision based on our existing data. We will retrieve that decision into our Raspberry PI by providing required data from SenseHAT (temperature and humidity) and AWS will tell us if we need watering or not based on our predefined data. To achieve this we will do following tasks -

1. Preparing training data
2. Train AWS AI
3. Prepare AWS to serve data
4. Retrieve predictive data into Raspberry Pi

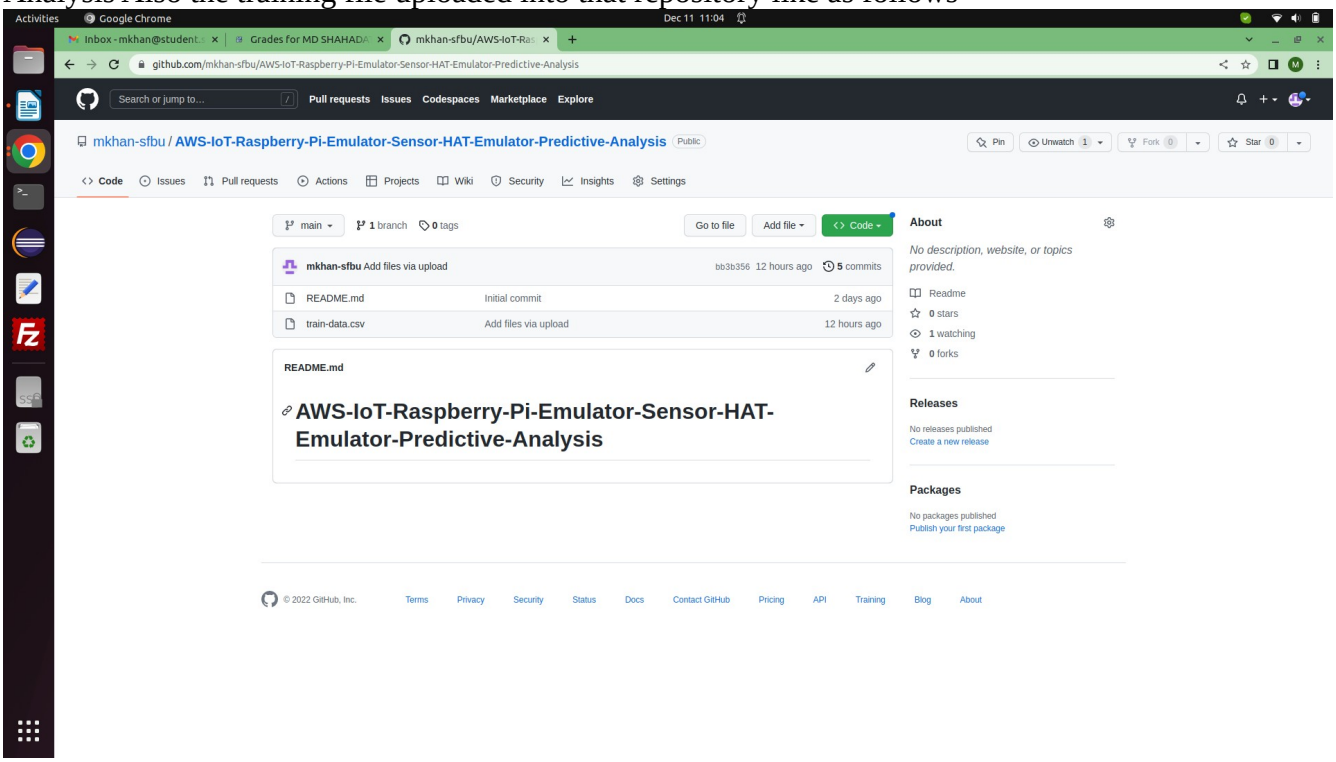
Preparing training data

To train AWS AI, we may use any logical data. Here I use data from https://followpearl.mit.edu/data/ in this page click on "download the latest seven days of data in a JSON format". After downloading it we need to convert this into CSV file. To do this visit https://data.page/json/csv and upload our JSON file and it will provide CSV file of that JSON file.

Now there you will find many columns, I just delete all columns but temperature and humidity column. I add another column labeled as “watering” and fill up “watering” column data by “y” or “n” based on some understanding of my own like maintain a ration between temperature and humidity value. Also we need to careful that there must remain NO space between rows and I delete non-numeric or empty row from this CSV file.



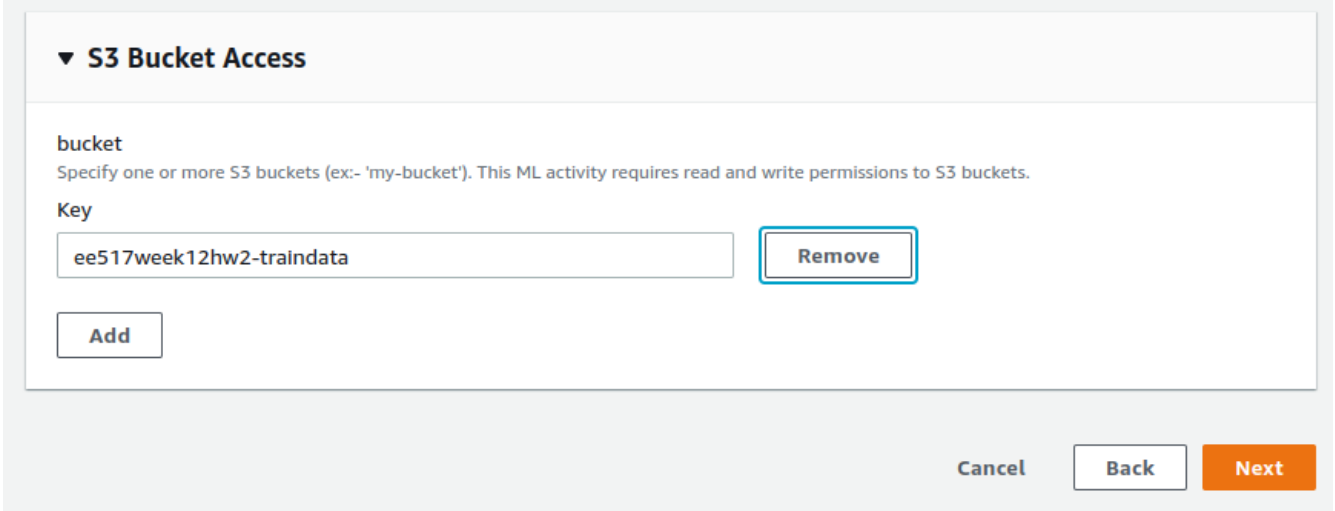
Our file is ready for training AWS AI. At this stage we need this file to be downloaded from internet, so I create a public github repository and put that file into repository. Here is the repository link https://github.com/mkhan-sfbu/AWS-IoT-Raspberry-Pi-Emulator-Sensor-HAT-Emulator-Predictive-Analysis Also the training file uploaded into that repository like as follows -



Now we have public downloadable link of our training data which we need later.

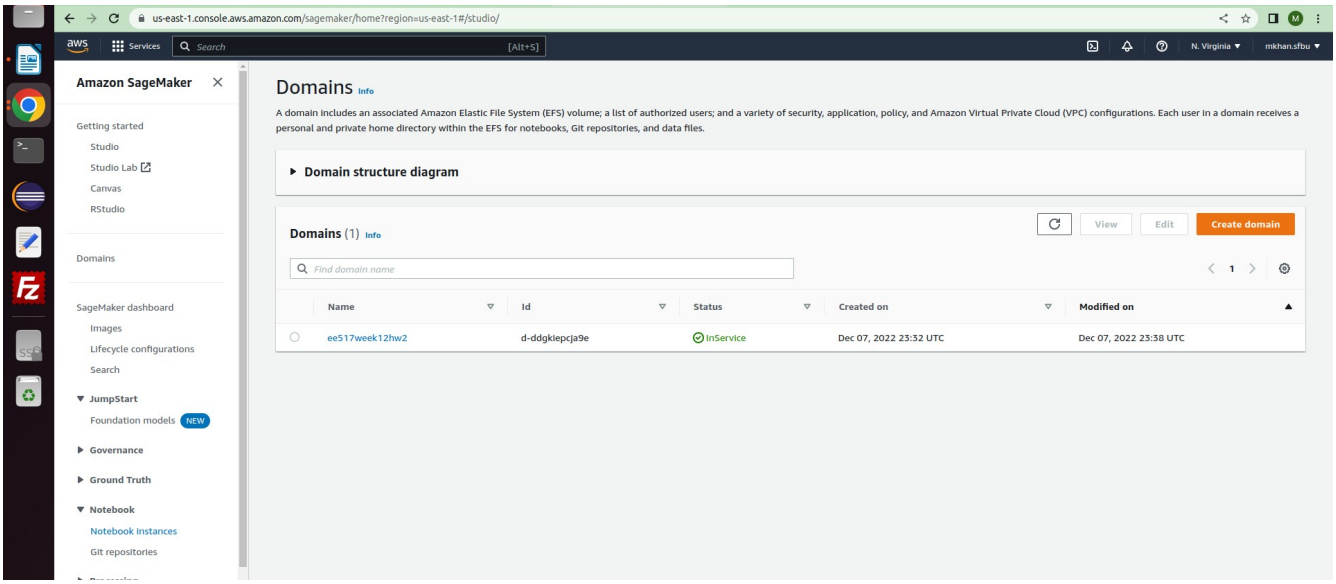
Train AWS AI

To train AWS AI we need some space where our filtered train data need to store. Also we need machine to run train script, here we use SageMaker Notebook of AWS. First of all we need to create a S3 bucket to store our training data. As we created bucket already before for our previous homework, I'm not going to show in details here.

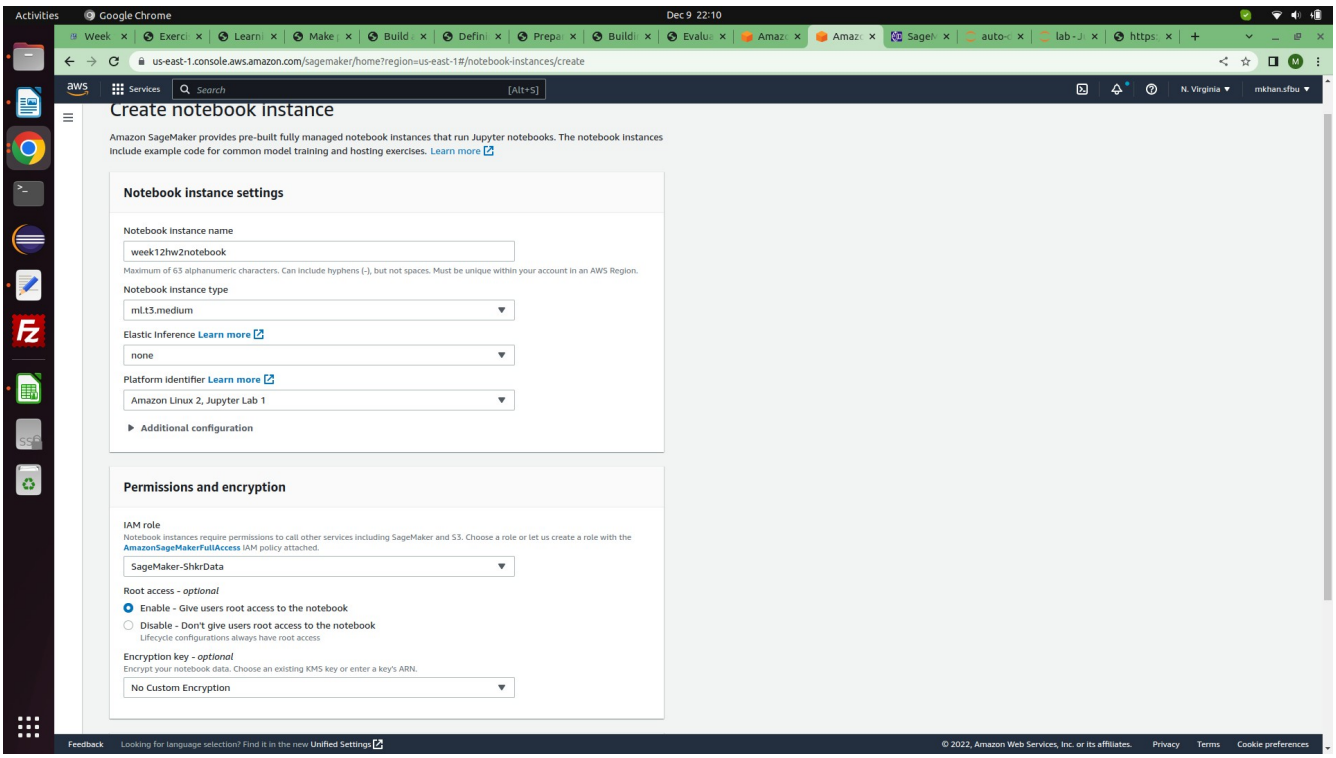


We created S3 bucket named “ee517week12hw2-traindata”. Now we are going to create SageMaker Notebook Instance and we are going to use it for training purpose.

To create SageMaker Notebook Instance first go to “SageMaker” but searching at the top search panel of AWS console. Then open “Notebook” drop down link from left menu and then click “Notebook Instances”. Please note, this instance means the virtual machine which managed by AWS. You can execute python code and any code by SSH login.

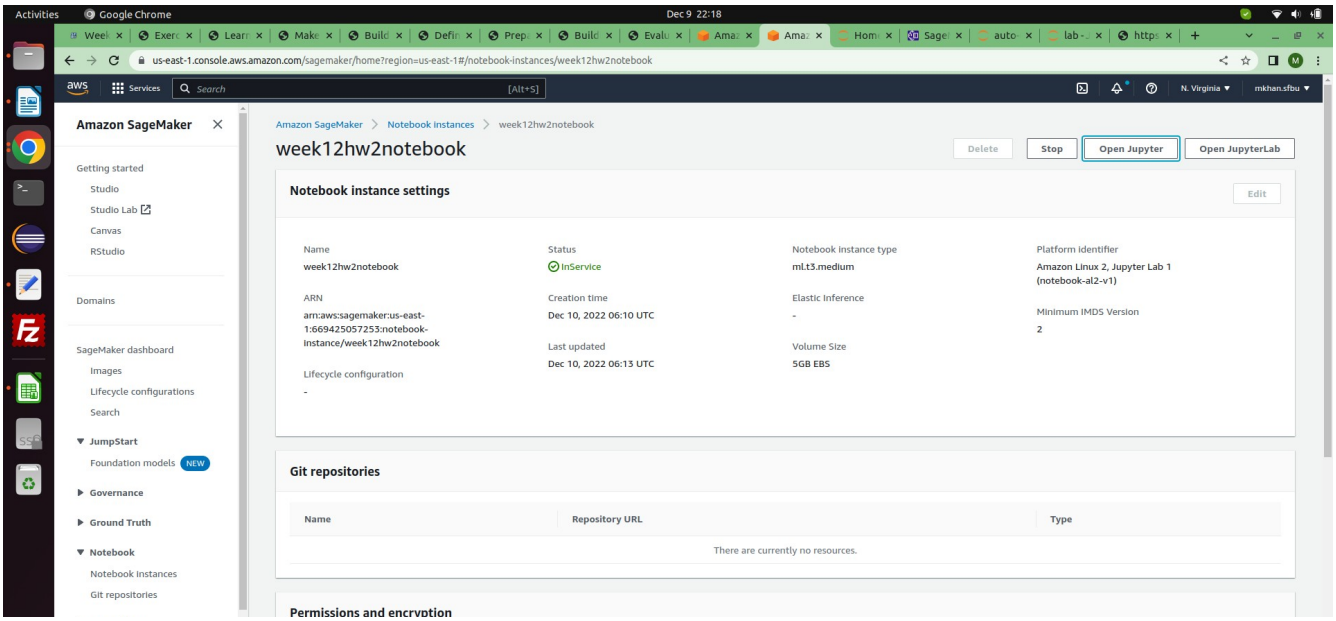


In that page you will find “Create Notebook Instance” link at top right corner, click on that link will land following page -

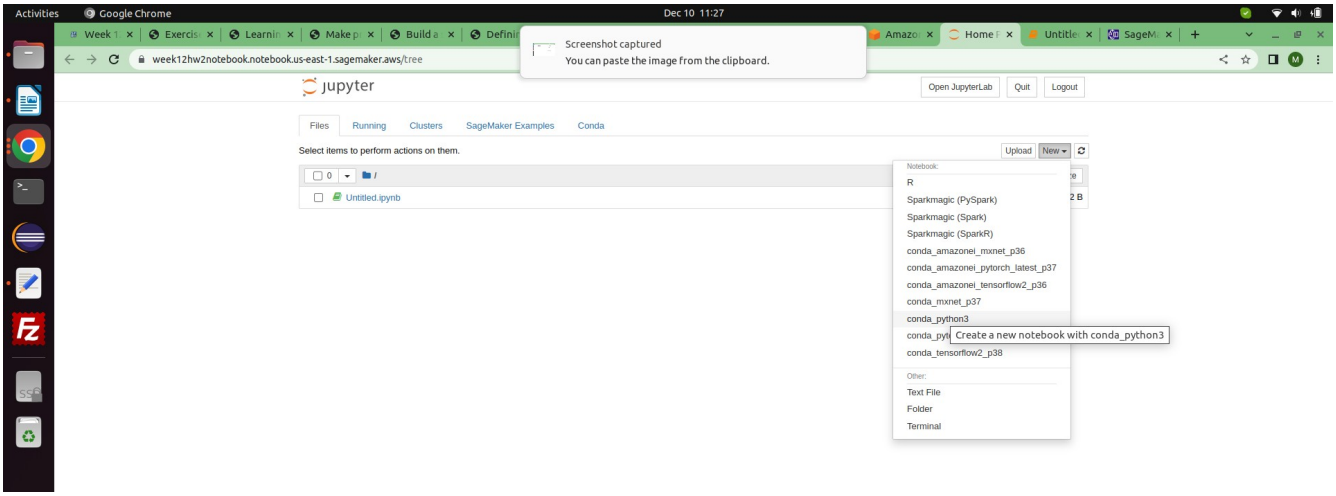


Input name of notbook instance and select a IAM role, if you don't have any IAM role system will create a new one automatically for you. Just keep that role and keep all default value of this page and click "Create notebook instance" button from end of form.

After creating notebook instance we need to wait a bit until status said "InService" as bellow -

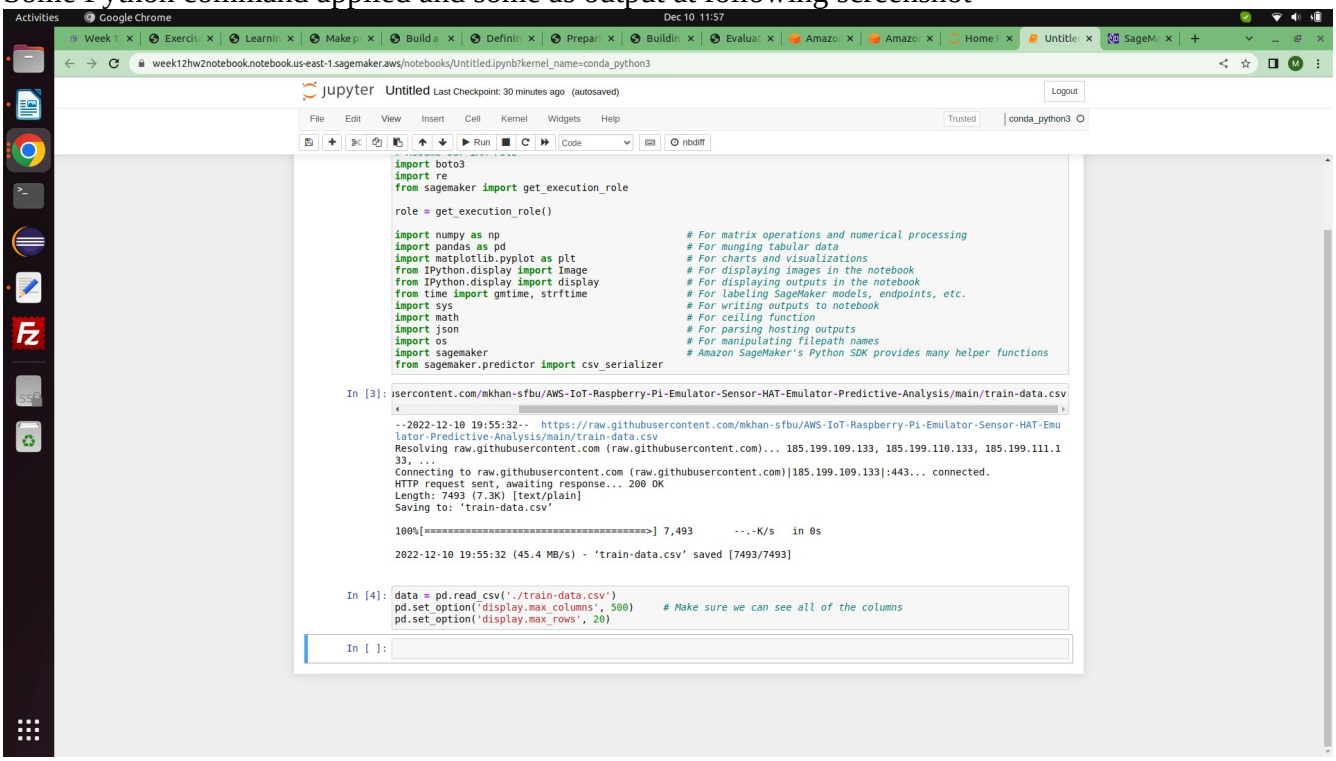


After getting "InService" status we need to click "Open Jupyter" button from top right panel. This will open Jupyter control panel for this instance in a new tab as follows -



From this page we need to open new "conda_python3" module to run our python code for training. We can find that link from "New" drop down link of top right corner. When we click this link, it will open a new Python code editor in a new tab. Basically it's a Python code executor by which we will train AWS AI and create model for our training data through. We are going to apply a bunch of Python code by typing, coping or pasting. Here we need to execute each code either by clicking "Run" button at the top bar or we can press "Shift+Enter". After execute each python command, system will print output (if any) at the bottom of that command line.

Some Python command applied and some as output at following screenshot -



Here is the python codes that we use to train our model -

```
import boto3
import re
from sagemaker import get_execution_role
import numpy as np                                # For matrix operations and
numerical processing
import pandas as pd                               # For munging tabular data
import matplotlib.pyplot as plt                   # For charts and
visualizations
from IPython.display import Image                 # For displaying images in
the notebook
from IPython.display import display               # For displaying outputs in
the notebook
from time import gmtime, strftime                 # For labeling SageMaker
models, endpoints, etc.
import sys                                        # For writing outputs to
notebook
import math                                       # For ceiling function
import json                                       # For parsing hosting
outputs
import os                                         # For manipulating filepath
names
import sagemaker                                  # Amazon SageMaker's Python
SDK provides many helper functions
from sagemaker.predictor import csv_serializer

role = get_execution_role()
bucket = 'ee517week12hw2-traindata'
```

```
prefix = 'notebookprefix'
```

We need our training CSV file which we stored into github! Following command will download that file from github -

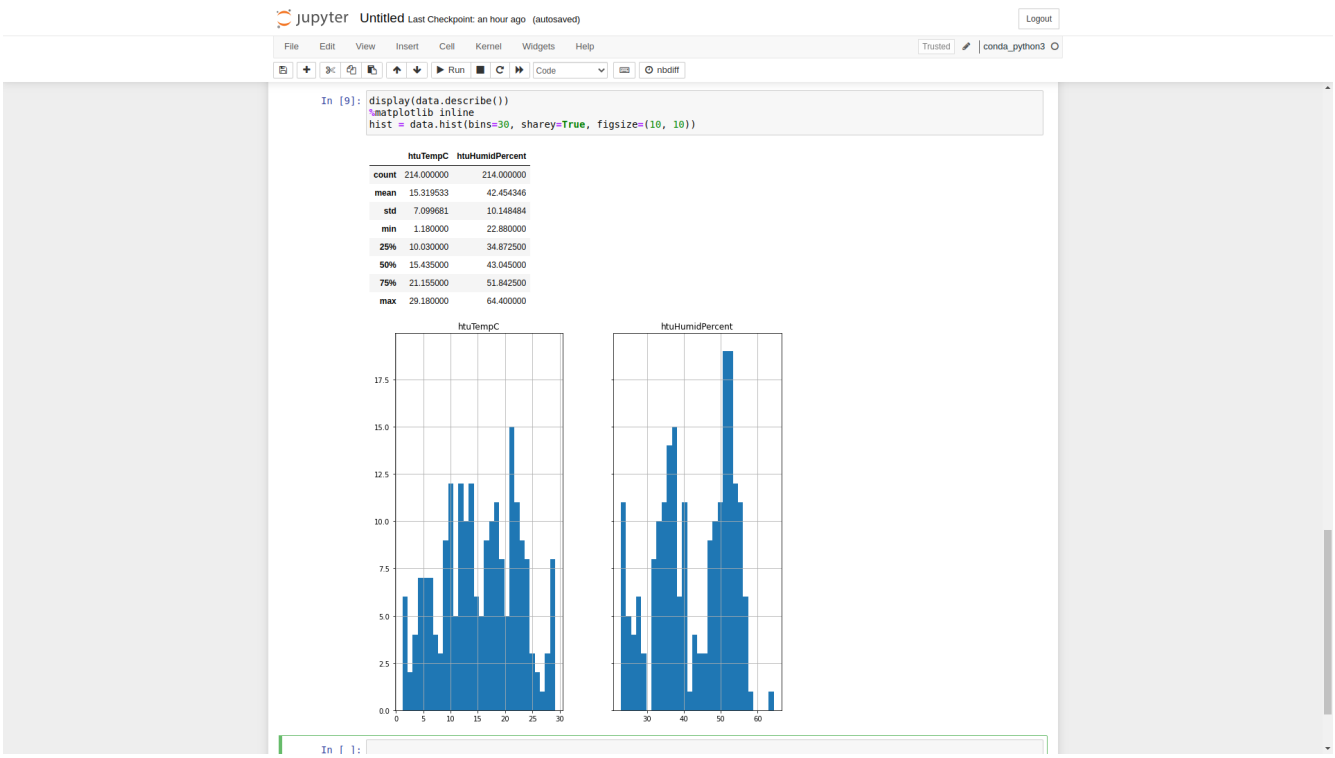
```
!wget https://raw.githubusercontent.com/mkhan-sfbu/AWS-IoT-Raspberry-Pi-Emulator-Sensor-HAT-Emulator-Predictive-Analysis/main/train-data.csv
```

Now we are going to use that downloaded file by loading through pandas.

```
data = pd.read_csv('./train-data.csv')
pd.set_option('display.max_columns', 500)     # Make sure we can see all of the columns
pd.set_option('display.max_rows', 20)
```

We can display our data by using plot command as follows -

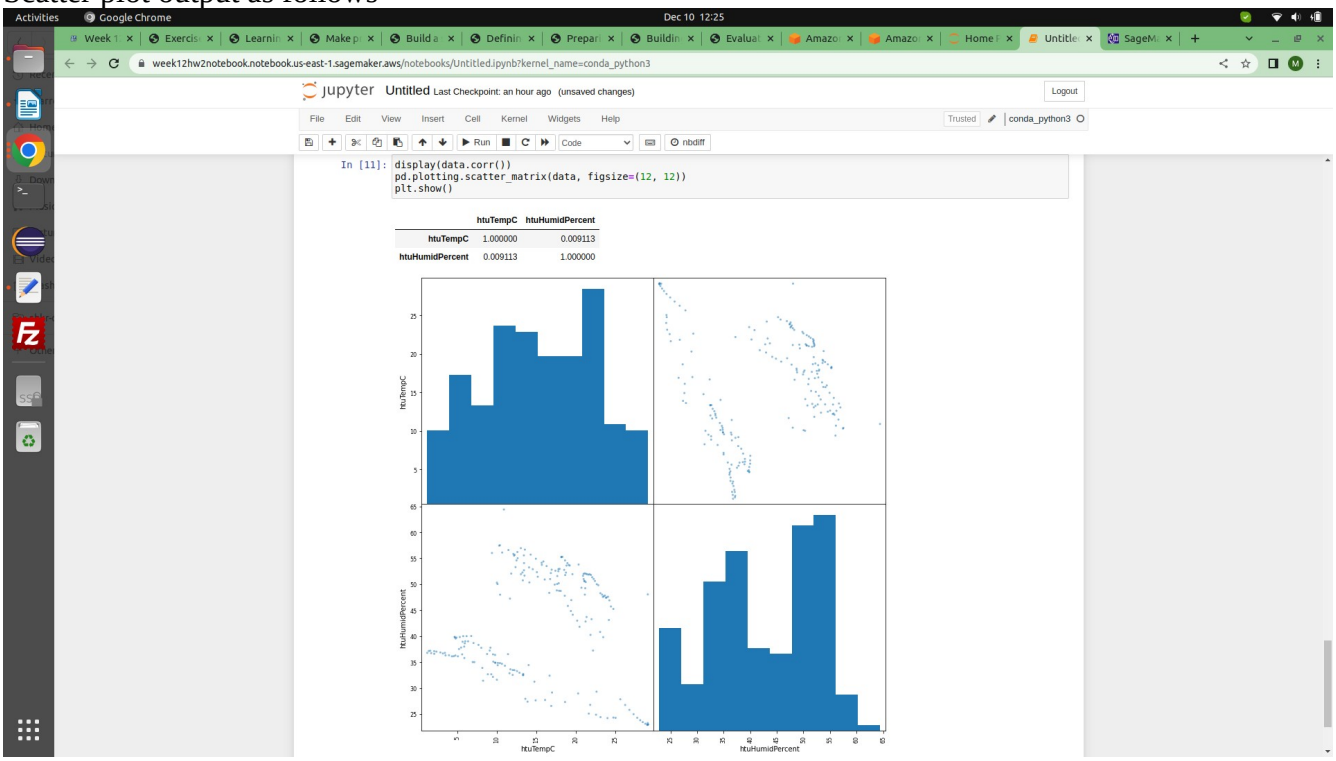
```
display(data.describe())
%matplotlib inline
hist = data.hist(bins=30, sharey=True, figsize=(10, 10))
```



By placing our data in a scatter plot, we essentially compare each feature in our dataset to itself and we're given an idea of how strong the correlation is between features. This only works for numeric features, hence why you won't be seeing our target variable in this plot.
To show our data in a scatter plot we used following commands -

```
display(data.corr())
pd.plotting.scatter_matrix(data, figsize=(12, 12))
plt.show()
```

Scatter plot output as follows -



So far we just view our data to ensure that we have valid relation between data. Now we are going to train AWS AI and create model based on our data. First we convert our data in training format then we split it into three data set randomly which are train data, validation data and test data. As our data is not real we may get error while validation later on. Though I'm showing the process how one can split data for specific purpose. Here is the commands to apply! -

```
model_data = pd.get_dummies(data) # pandas read raw data and prepared
train_data, validation_data, test_data = np.split(model_data.sample(frac=1,
random_state=1729), [int(0.7 * len(model_data)), int(0.9 * len(model_data))])
```

Now we are going to store train and validation data. Please note we need to mention target variable in the first column. Here we target/predict "watering" column whee value is either "y" or "n" so final target column is "watering_y". Following command will store our data into our desired file name -

```
# Prep the training set for the XGBoost algorithm - the target variable must
be the first column and store the dataset as a CSV
pd.concat([train_data['watering_y'], train_data.drop(['watering_n',
'watering_y'], axis=1)], axis=1).to_csv('train.csv', index=False,
header=False)
# Same as above for the validation set
```

```
pd.concat([validation_data['watering_y'], validation_data.drop(['watering_n',
'watering_y'], axis=1)], axis=1).to_csv('validation.csv', index=False,
header=False)
```

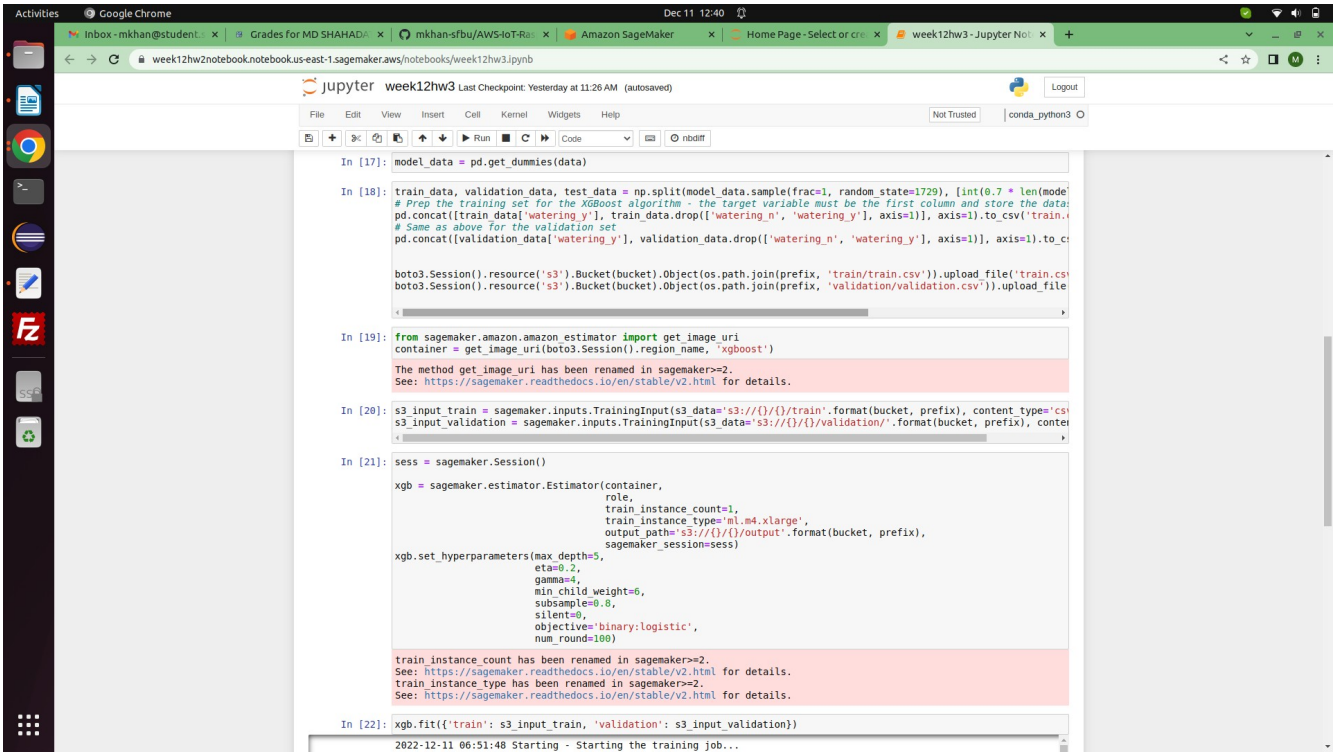
Now we are going to store train and validation data into S3 bucket. So, our AI also can get those file easily when required. We will get help of boto3 project to communicate between our Python script and AWS S3 bucket. As previous we already set our bucket name, we are going to use here. Also we set prefix, so system will create folder into S3 bucket and will put those file into that folder.

```
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix,
'train/train.csv')).upload_file('train.csv')
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix,
'validation/validation.csv')).upload_file('validation.csv')
```

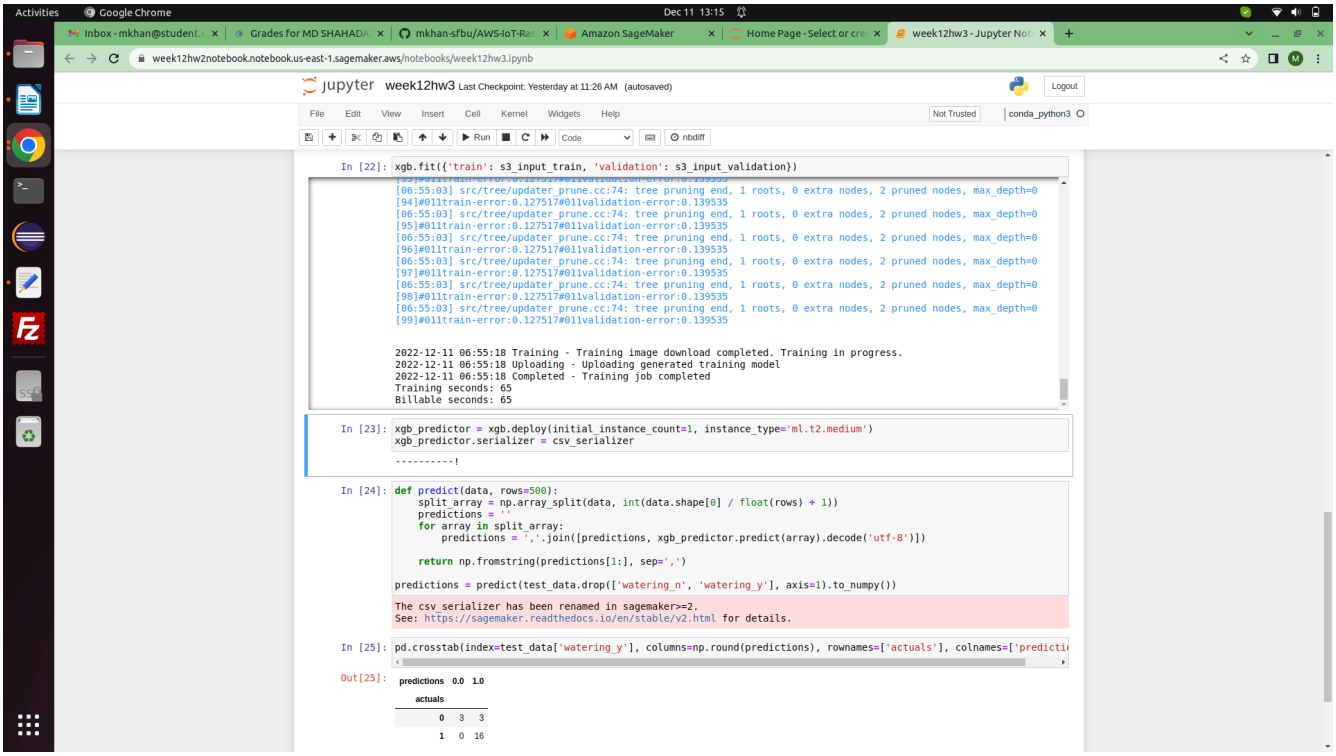
At this stage we are going to open SageMaker session to train model with out data by using following commands -

```
sess = sagemaker.Session()

xgb = sagemaker.estimator.Estimator(container,
                                    role,
                                    train_instance_count=1,
                                    train_instance_type='ml.m4.xlarge',
                                    output_path =
's3://{}/{}/output'.format(bucket, prefix),
                                    sagemaker_session=sess)
xgb.set_hyperparameters(max_depth=5,
                        eta=0.2,
                        gamma=4,
                        min_child_weight=6,
                        subsample=0.8,
                        silent=0,
                        objective='binary:logistic',
                        num_round=100)
xgb.fit({'train': s3_input_train, 'validation': s3_input_validation})
```

Here is the output of above codes -



After finish execution of above code the output will show as follows. Please note that on “Ln [22]” you will see like “Ln [*]” while executing code. After finish complete it shows the line number. This is important that we need to wait till complete. After code execution finish we will apply further commands.



After finish our training we need to deploy our model, so that we can get predictive result for our IoT devices. Please note, after finishing deployment one endpoint for this deployment will create

automatically at SageMaker control panel, which we need later and will retrieve later. Here is the deploy code -

```
xgb_predictor = xgb.deploy(initial_instance_count=1,
instance_type='ml.t2.medium')
```

This deploy also need some time, we have to wait to apply further command. After finishing deployment we can check our deployment through our test data by following commands -

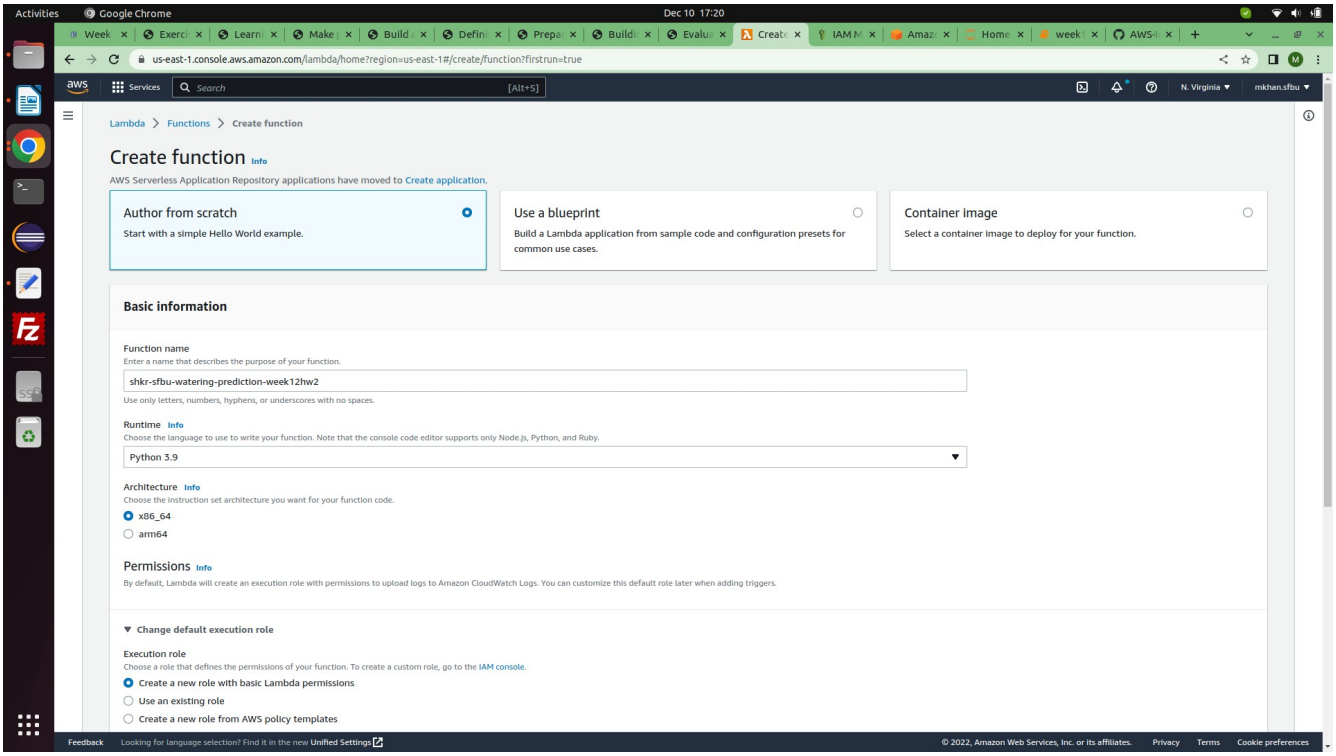
```
xgb_predictor.serializer = csv_serializer
def predict(data, rows=500):
    split_array = np.array_split(data, int(data.shape[0] / float(rows) + 1))
    predictions = ''
    for array in split_array:
        predictions = ','.join([predictions,
xgb_predictor.predict(array).decode('utf-8')])
    return np.fromstring(predictions[1:], sep=',')

predictions = predict(test_data.drop(['watering_n', 'watering_y'],
axis=1).to_numpy())

pd.crosstab(index=test_data['watering_y'], columns=np.round(predictions),
rownames=['actuals'], colnames=['predictions'])
```

Output of above code is shown in above screenshot. That’s all we are ready to get data into our IoT devices, but for this we need to go through some process in AWS.

Prepare AWS to serve data

We do ready our model for prediction, now we need to get that predictive data into our IoT devices. To do this we need to create a lambda function of AWS which responsible for grab data from our SageMaker model. Then we need to create a REST API service at AWS which will execute that lambda function and send the result as a response of REST API request.

To create lambda function search lambda at the top search bar of AWS consol and then create lambda dashboard, at that dashboard you will find “Create function” link. After clicking that link it will open following page. Here just input name of the function and select runtime as “Python 3.9”. Select your architecture, mine is “x86_64” and select “Create a new role with basic Lambda permissions” into execution role section. Leave all other as is and click “Create” button from bottom of page.

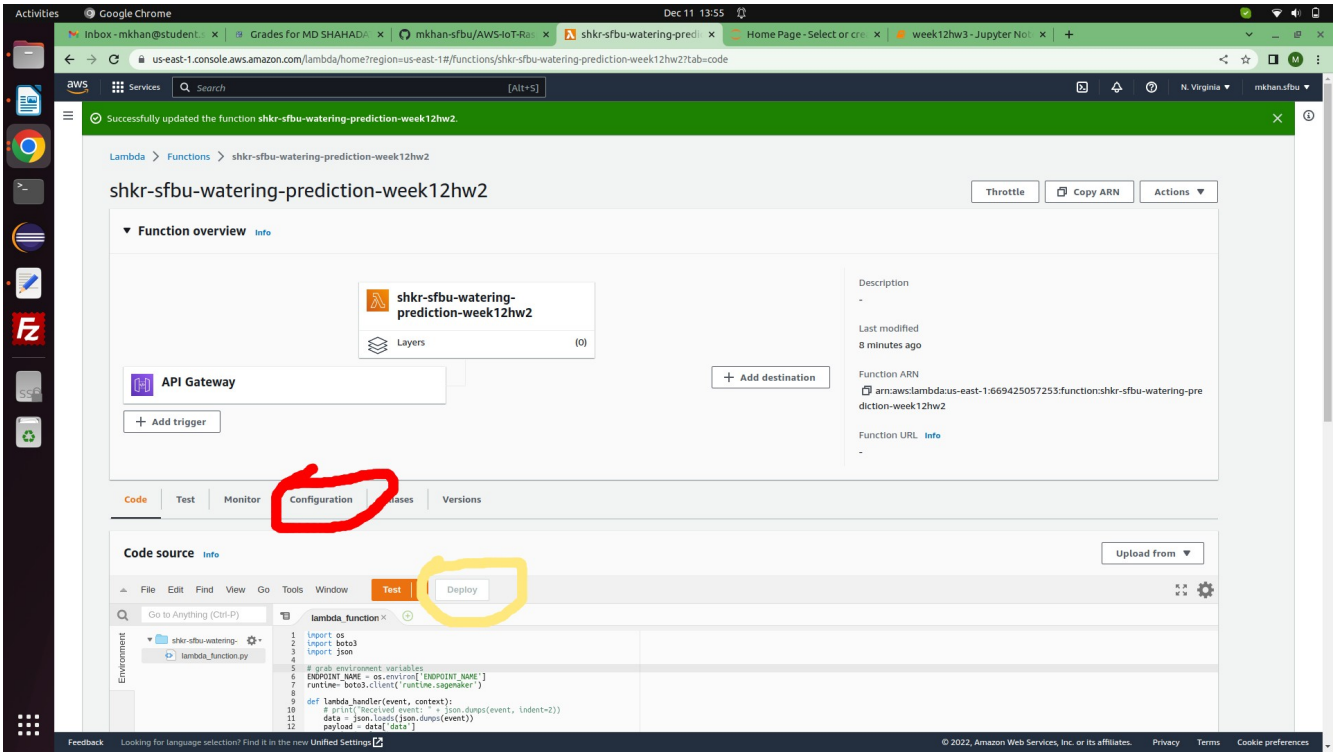


Dashboard of Lambda function we created will show and with code editor to put following code.

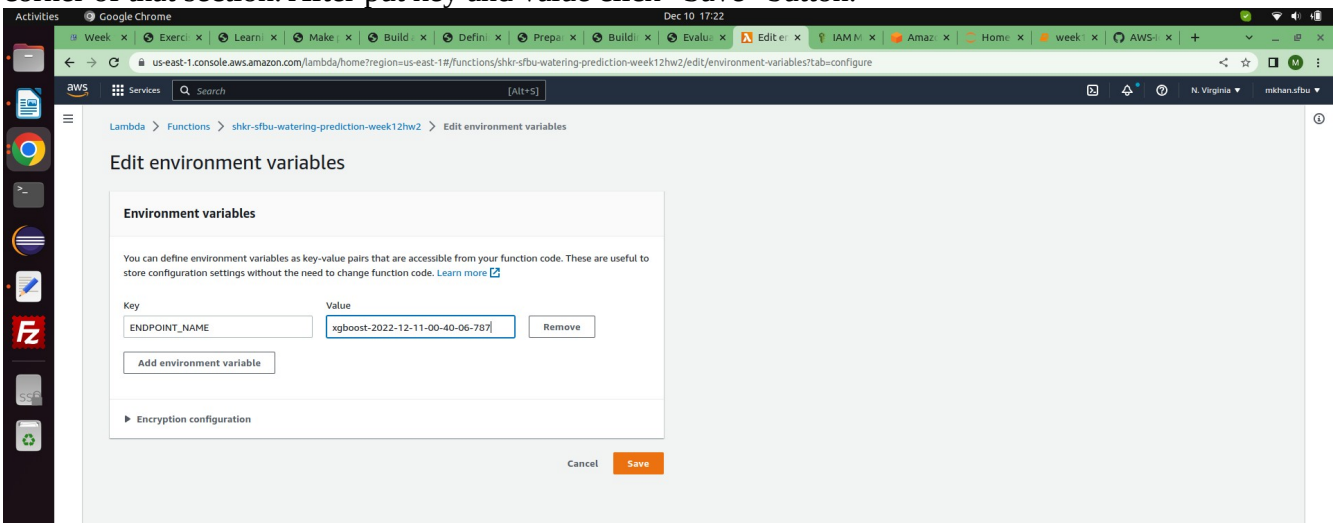
```
import os
import boto3
import json
ENDPOINT_NAME = os.environ['ENDPOINT_NAME']
runtime= boto3.client('runtime.sagemaker')
def lambda_handler(event, context):
    data = json.loads(json.dumps(event))
    response = runtime.invoke_endpoint(EndpointName=ENDPOINT_NAME,
                                       ContentType='text/csv', Body=data['data'])
    result = json.loads(response['Body'].read().decode())
    return 'W' if float(result) > 0.5 else 'X'
```

It’s a simple code, we get our SageMaker model endpoint name from environment variable. Into lambda_handler method we invoke our endpoint by providing payload and after that we load model response into json module and decode it for our result. Here as our data is not good we get result between 0 ~ 1. So, I response “W” means need watering if we have result 50% positive otherwise returns “X”. This 50% I assumed from based on my data, anyone can play with this percentage.

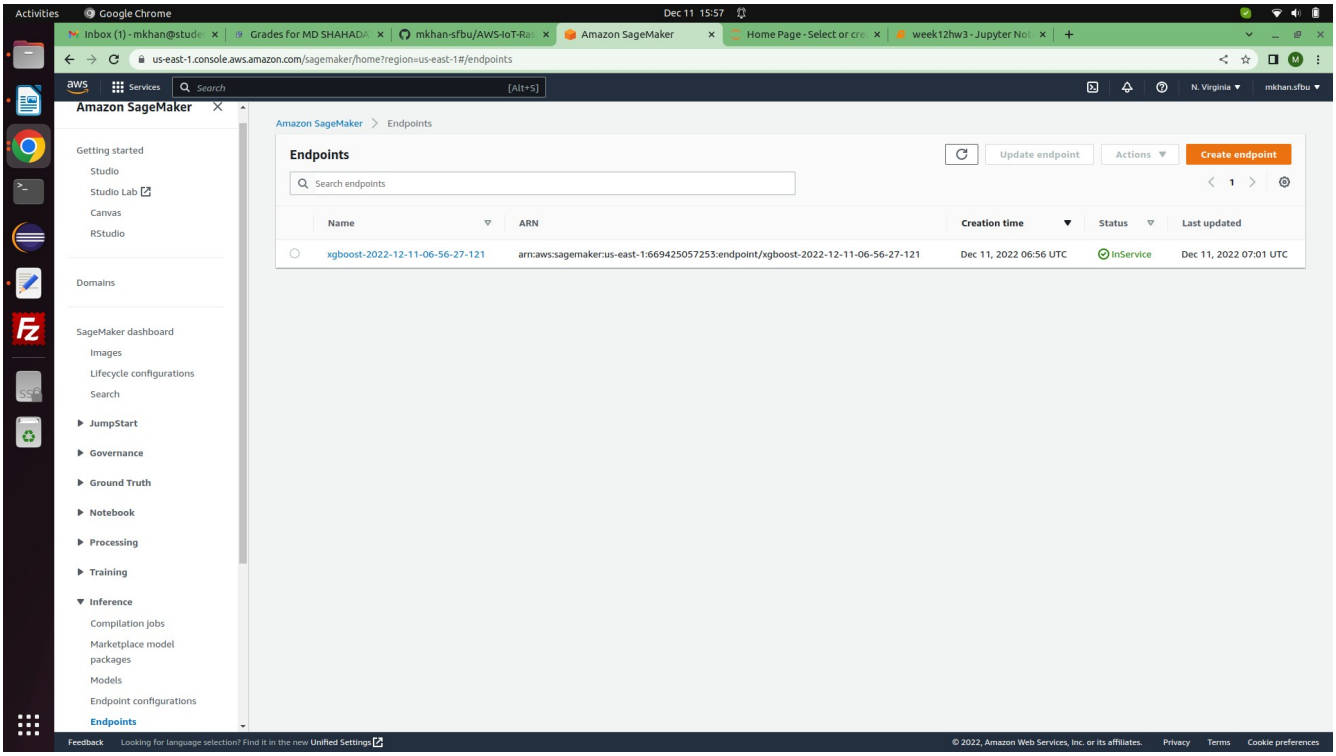
Here is the interface screenshot. Note that we need to save our code by clicking “File > Save” at editor. After saving code we need to deploy by clicking “Deploy” (will active when we change code) button at editor menu bar (yellow marked).



Now two major things is how to set environment variable that required to execute this command. To set environment variable click “Configuration” link (red marked in above screenshot) then click “Environment variables” link at the left side menu. Into that page click “Edit” button from right top corner of that section. After put key and value click “Save” button.

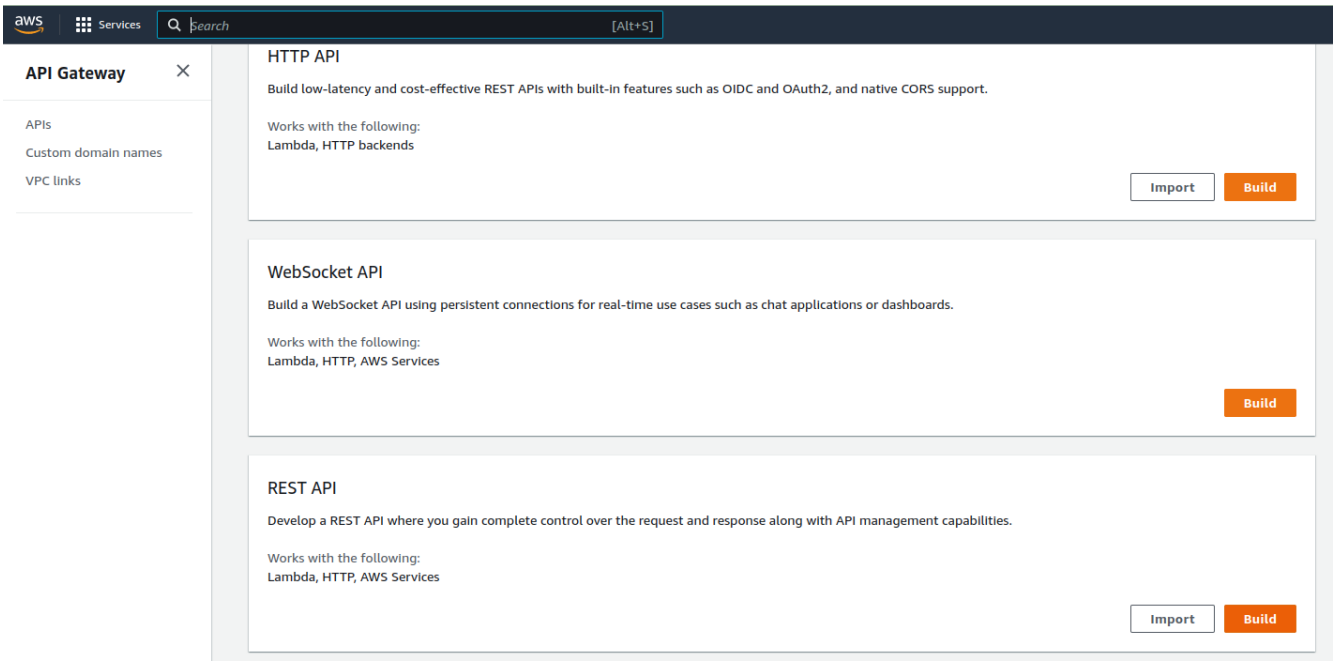


Before going environment variable settings we need SageMaker deployment endpoint name. To get that name we need to go SageMaker dashboard and then need to open “Inference” link from left menu and click on “Endpoints” from the list. Here we will get all available endpoints of our project. Here we found our endpoint that automatically generated from deployment code.

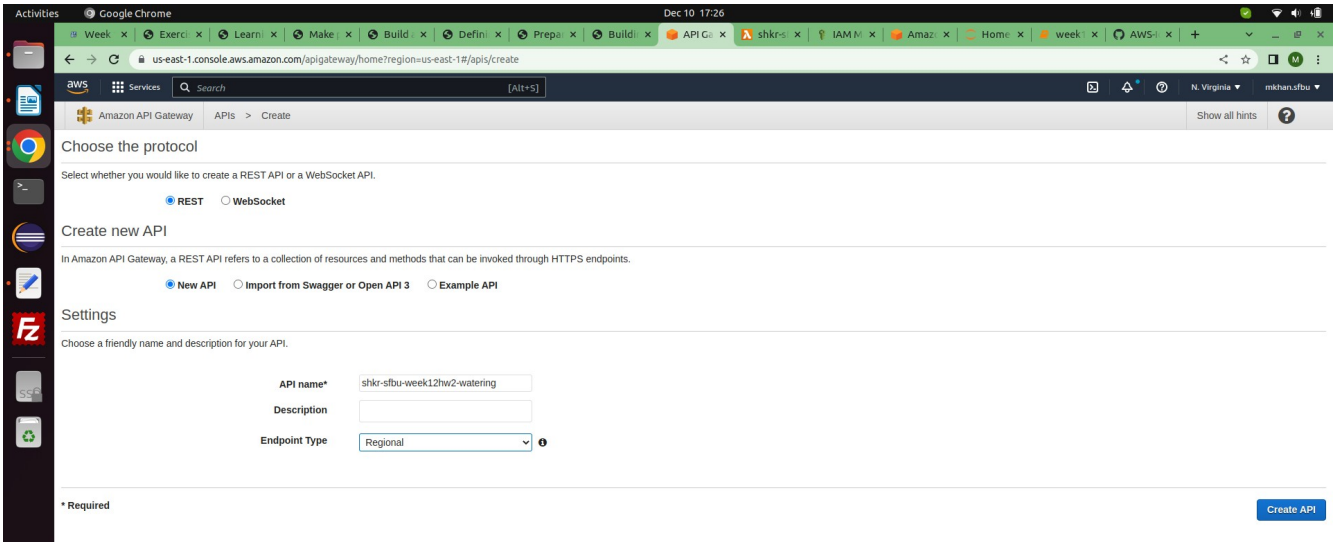


From endpoints list we can easily get endpoint name that need to use into environment variable above.

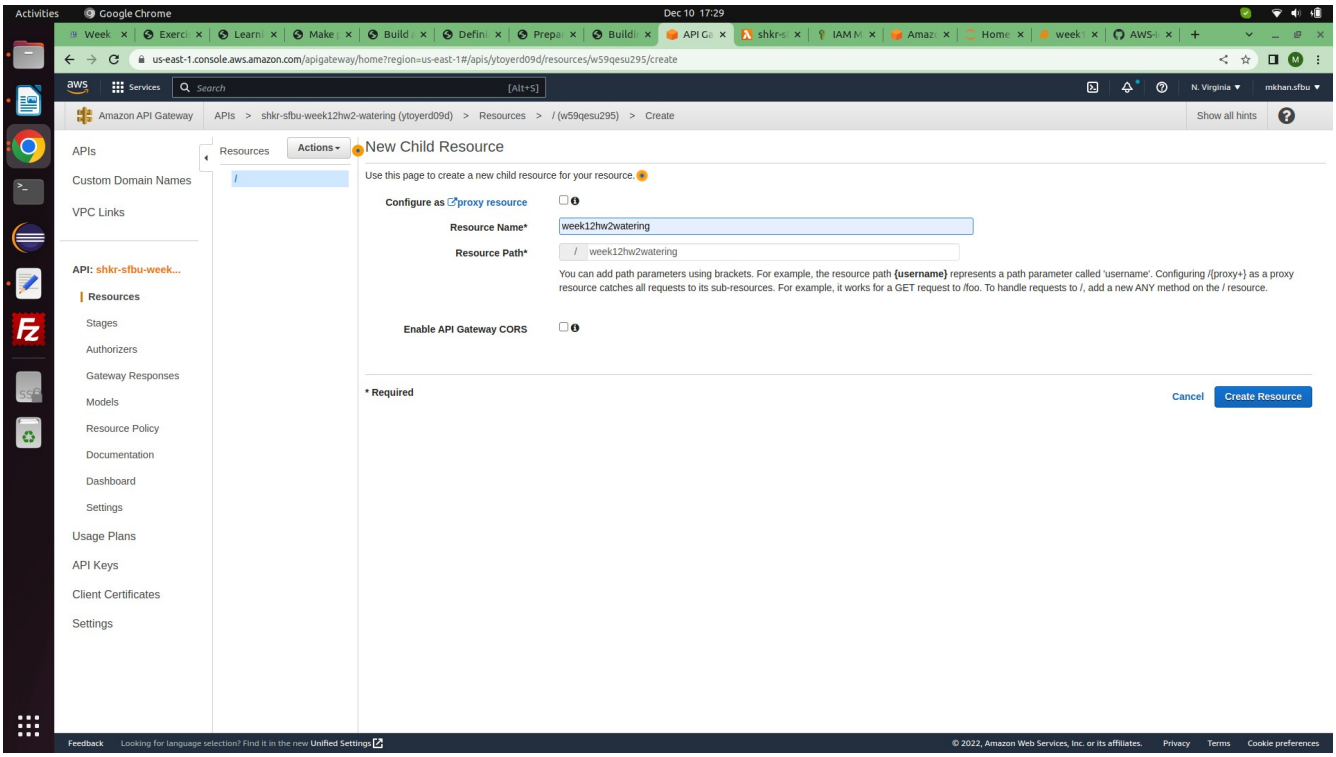
Lambda function completed, now we need to setup REST API. To do this search “rest” at the top search bar of consol you will get “API Gateway” link, click that link will land following dashboard -



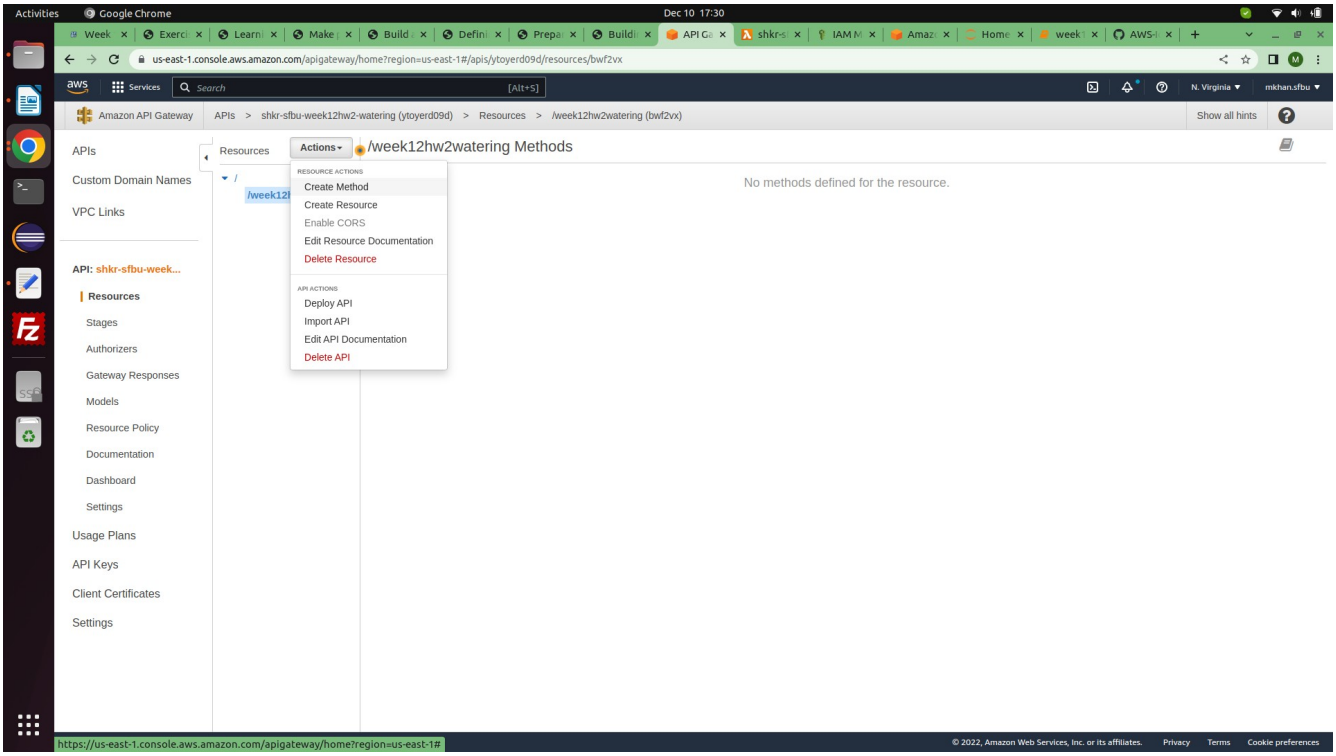
Clicking on “Build” button of REST API will open following page. Here we need to select “REST” and need to select “New API”. Also we need to provide a name of our API and need to select Endpoint Type which is “Regional” then we need to click “Create API” button at bottom right corner.



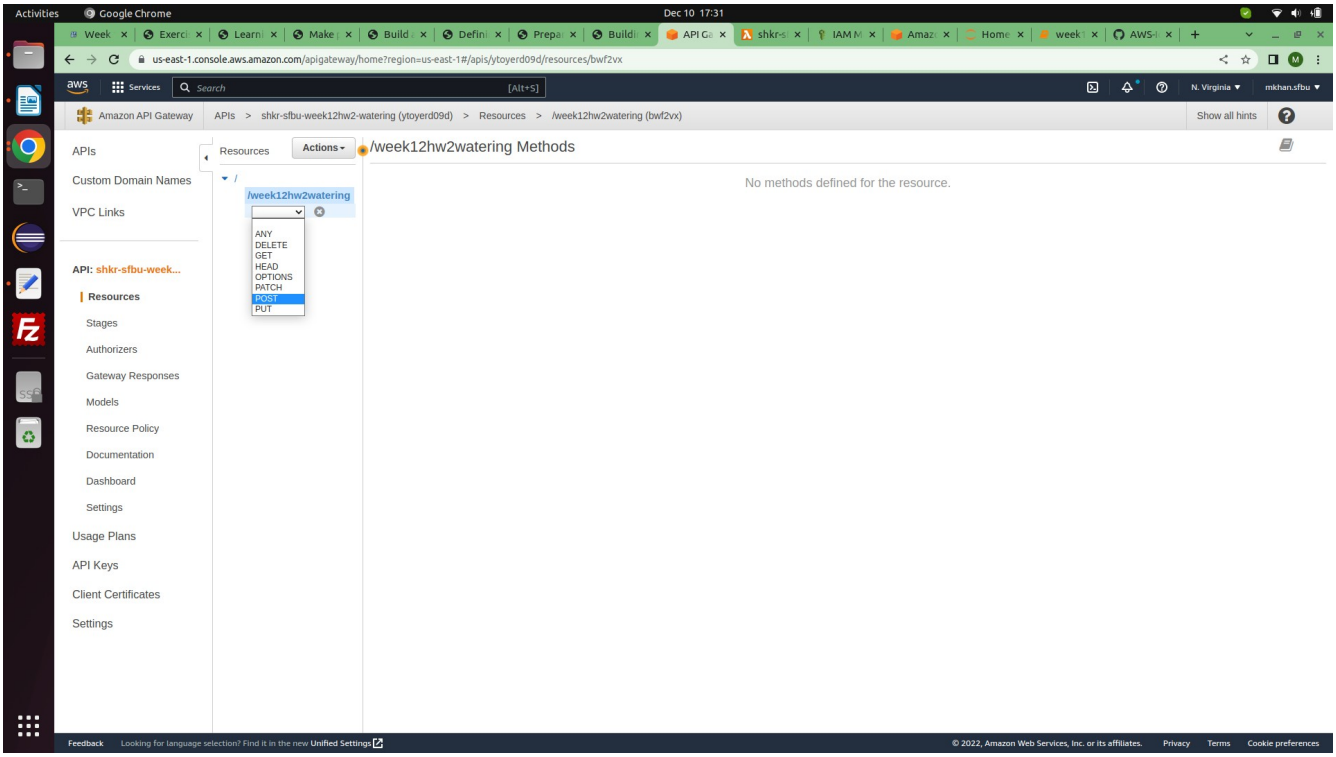
After creating API we need to click on “Action” drop down list and there we will find “Create Resource” link. Clicking on “Create Resource” link we will land on following page. Here we need to provide new resource name and need to click “Create Resource” link at bottom right corner.



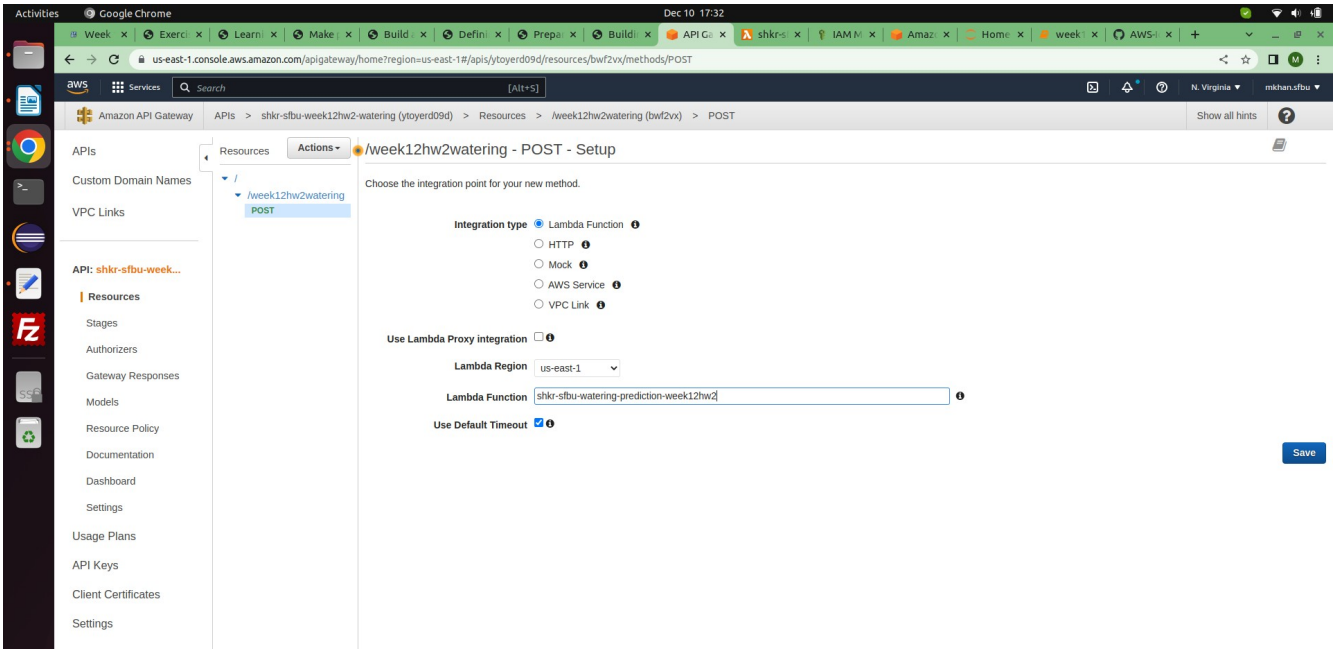
After creating resource, we need to create method (POST). Again we need to click on “Action” drop down button and we will find “Create Method” link. Please note, newly created resource will automatically selected but if it is not then, we have to select our resource at the middle section.



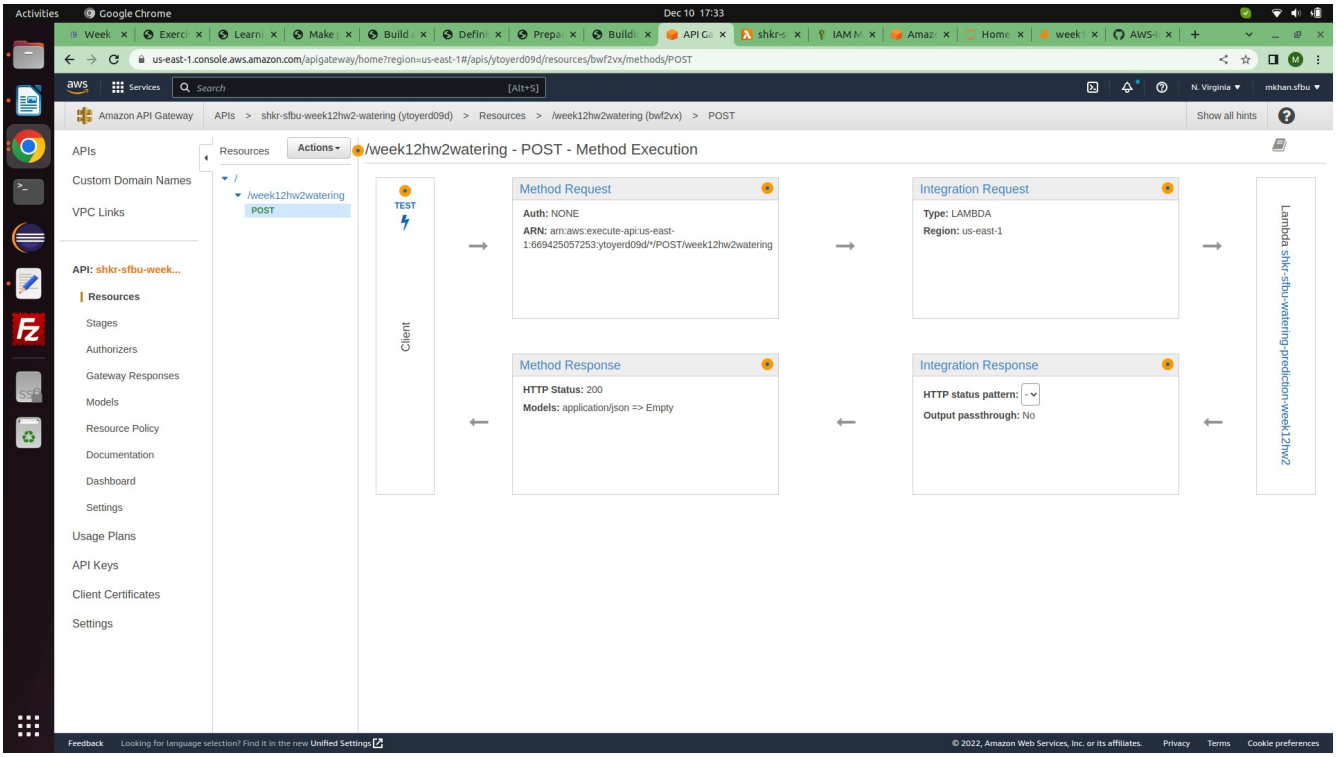
When we click “Create Method” we need to select which type of method we are going to create from drop down list as shown bellow. We are going to select “POST” method, cause we are going to query for our prediction result through POST method.



When we select “POST” method one page open to create this method. In this page we need to tell that we are going to execute “Lambda Functions” on this method invoke. And we need to provide that Lambda Function name. Please keep region and timeout setting as default. Finally click “Save”

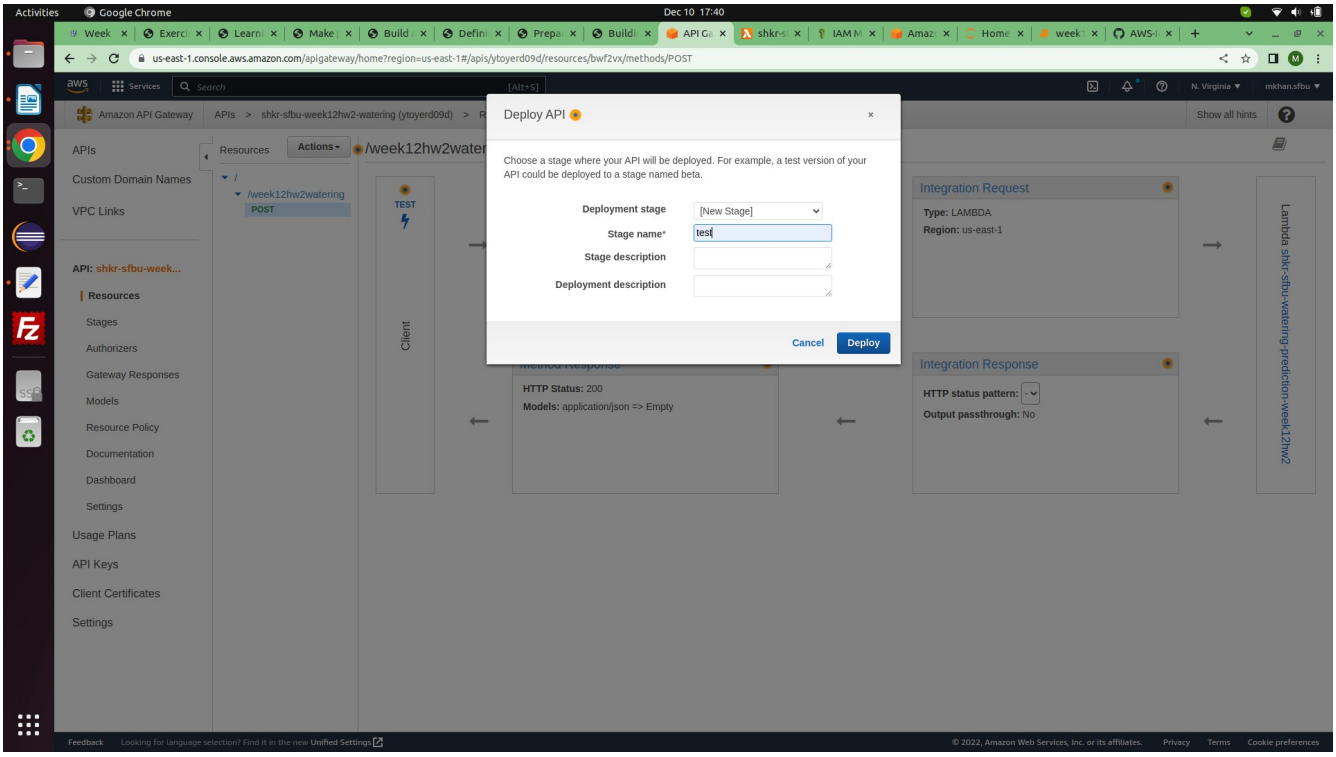


Following page will appear after finish our post method creation. At this stage we need to deploy our API. To do this click “Action” drop down again, there “Deploy API” link will found.

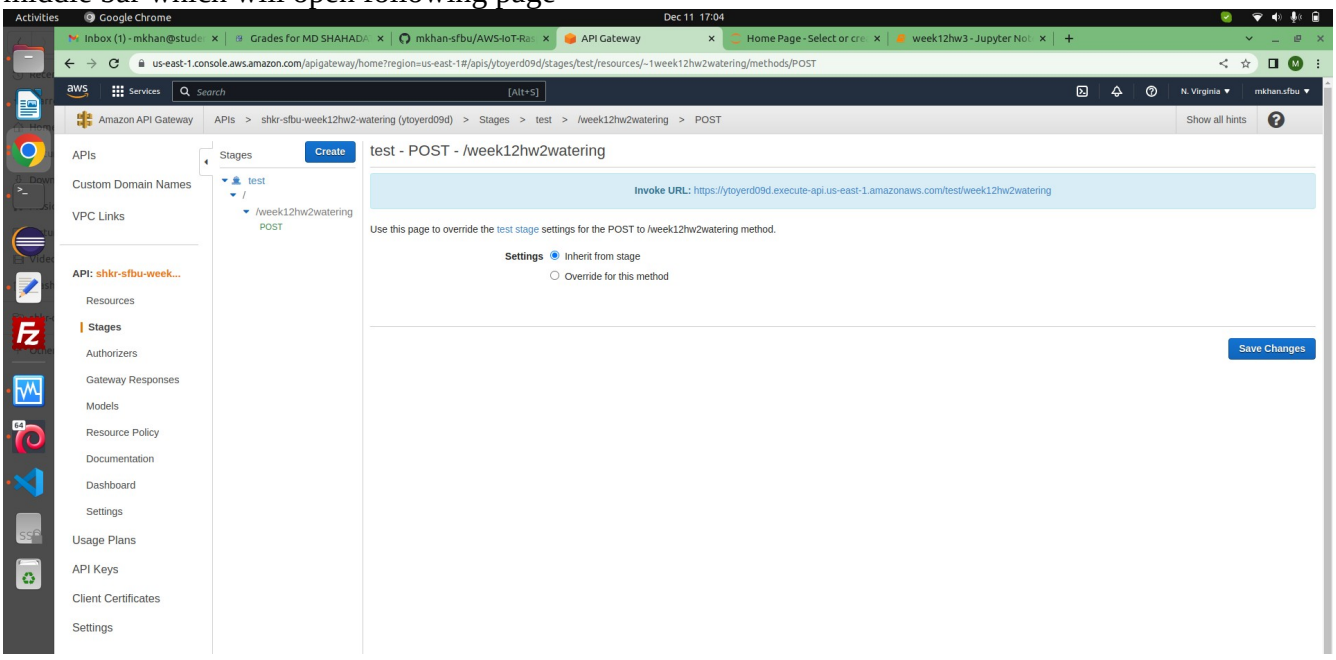


When we click “Deploy API” on popup box will appear from where we need to select “Deployment stage” as “[New Stage]” and then we need to provide stage name, here we provide “test” as its our test

deployment. And then click “Deploy” will deploy this API and we can start querying the API for predictive result.



That’s all from AWS configuration, we deployed API to get predictive result. Now we are going to query this API from our Raspberry Pi with SensorHAT data. To query to REST API we need API endpoint URL. To get the URL click on “Stages” link from left menu and select “POST” method from middle bar which will open following page -



From above page we need to copy/save “Invoke URL” to which we need to query from our device.

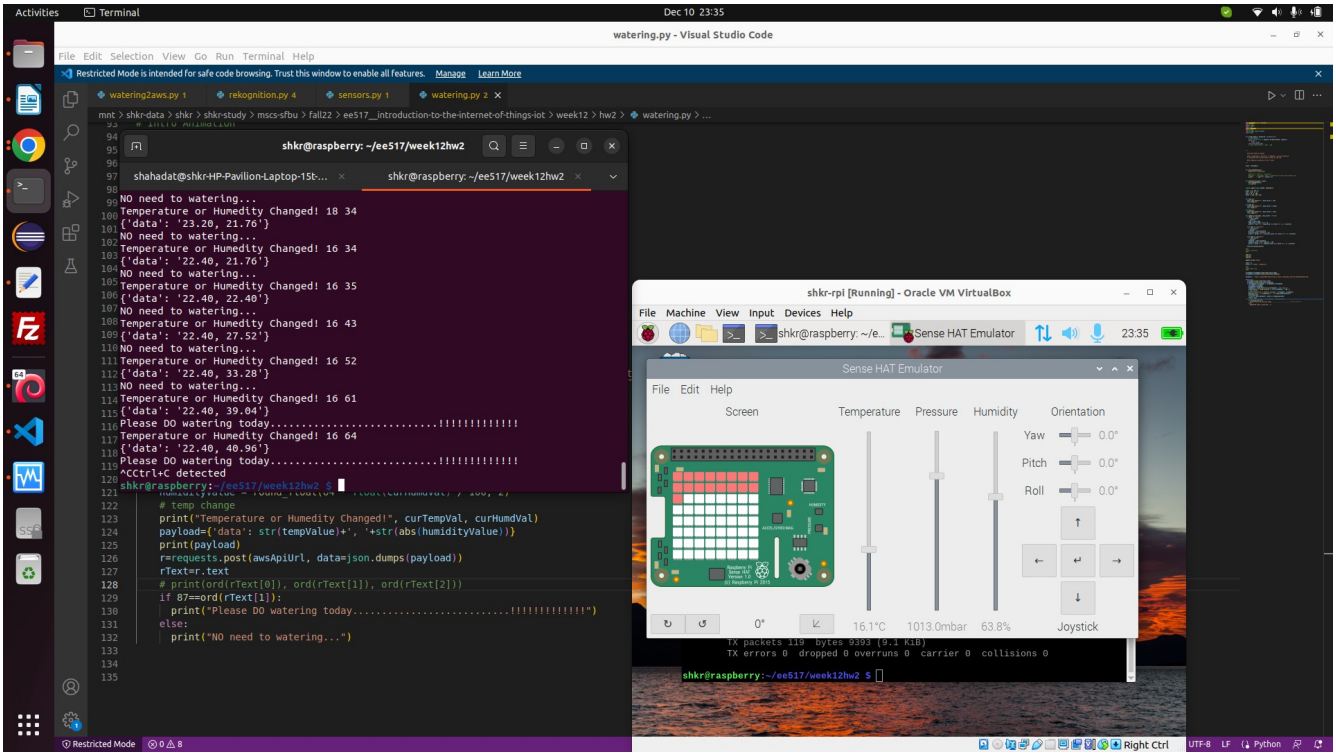
Retrieve predictive data into Raspberry Pi

As we need temperature and humidity data to query AWS for predictive result we are going to use SanseHAT emulator to get those data. Following Python code will query to AWS REST API and show appropriate message to user based on result which is if user need watering or not based on current temperature and humidity data.

```
from sense_emu import SenseHat
import signal
import sys
import requests
import json
from decimal import Decimal

def round_float(v, ndigits=0, rt_str=False):
    d = Decimal(v)
    v_str = ("{0:.%sf}" % ndigits).format(round(d, ndigits))
    if rt_str:
        return v_str
    return Decimal(v_str)

sense = SenseHat()

def destroyAndRelease():
    print("Ctrl+C detected")
    print("    ", end="\r", flush=True)


def handleExit(signum, frame):
    destroyAndRelease()
    sys.exit(1)


signal.signal(signal.SIGINT, handleExit)

prvTempVal=curTempVal=round_float(sense.temp)
prvHumdVal=curHumdVal=round_float(sense.humidity)

awsApiUrl =
'https://ytoyerd09d.execute-api.us-east-1.amazonaws.com/test/week12hw2watering
'

while True:
  curTempVal=round_float(sense.temp)
  curHumdVal=round_float(sense.humidity)
  if prvTempVal!=curTempVal or prvHumdVal!=curHumdVal:
    prvTempVal=curTempVal
    prvHumdVal=curHumdVal
    tempValue = round_float(float(curTempVal) / 2.5 + 16, 2)
    humidityValue = round_float(64 * float(curHumdVal) / 100, 2)
    print("Temperature or Humedity Changed!", curTempVal, curHumdVal)
    payload={'data': str(tempValue)+', '+str(abs(humidityValue))}
    print(payload)
    r=requests.post(awsApiUrl, data=json.dumps(payload))
    rText=r.text
    if 87==ord(rText[1]):
```

```
        print("Please DO watering
today.....................!!!!!!!!!!!!!")
    else:
        print("NO need to watering...")
```

Above code are pretty straight forward, here we check temperature and humidity data change in a infinity while loop. Before execute that loop we setup “Ctrl+C” trap, so if user press “Ctrl+C” our program will terminate. And we query to our API by Python’s “requests” module. If we get result we comparing and show user like “No need to watering…”. Here is our program in action -



Code Repository: https://github.com/mkhan-sfbu/AWS-IoT-Raspberry-Pi-Emulator-Sensor-HAT-Emulator-Predictive-Analysis

Thank You